Contagious loan default*

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Abstract

Applying survival analysis to a large loan-level dataset for regulatory purposes on group loans provided by Mexican banks, I find that ex-post credit risk is subject to substantial geographic spillover effects. Potential underlying mechanisms include contagious defaulting behavior, which bears the risk of proliferating into a repayment crisis in the event of an economic or political shock, as experiences from similar markets suggest.

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1 Introduction

Several default crises have shaken up the microfinance sector over the past decade.¹ While underlying market conditions and crisis triggers varied, a common observation was that default rates began to mount locally and eventually spread across the market. This study investigates the role of geographic spillovers in transmitting credit risk by applying a Cox regression model to a large panel dataset of group loans in Mexico from 2012 to 2017. The results confirm that geographic spillovers within a neighborhood substantially add to credit risk.

Micro-level geographic spillovers, which are typically linked to network effects, have been traced in different contexts of financial decision-making, such as stock trading behavior (Hong et al., 2005), mortgage defaults (Gupta, 2016), or bank runs (Iyer and Puri, 2012; Kiss et al., 2014). In microfinance, network effects are usually studied in the context of group lending, with a focus on a borrower’s repayment behavior vis-à-vis her loan group (Cassar et al., 2007; Allen, 2016; Breza, 2012; Katzur and Lensink, 2012).² In contrast, no systematic evidence is available about geographic transmission of credit risk *beyond* loan groups. Banerjee et al. (2013) observe in an Indian context that word-to-mouth information flowing between potential borrowers across villages substantially explains the uptake of microfinance products; arguably, such network effects may extend to credit risk as well. Bond and Rai (2009) show theoretically how strategic defaults can contaminate the entire market when borrowers, observing each others’ actions, expect the repayment performance of other borrowers to deteriorate.

In Mexican microfinance, unlike in other Latin American countries, group lending continues to be the dominant lending method, mainly because restrictive regulations have curbed the expansion of individual microlending (WWB, 2014). Accounts of widespread over-indebtedness among borrowers raise concerns among practitioners that the market may be the next to be heading towards a default crises.³ A case in point is Mexico’s own history with “borrower runs”: following a dramatic peso devaluation in 1994 that preceded an economic crisis, Mexican borrowers defaulted strategically, anticipating that loan repayment would not prevent lenders, who had already seen their asset positions

¹Most prominently in the Indian state Andhra Pradesh (Mader, 2013), Nicaragua (Servet, 2015), Bosnia and Herzegovina (Augsburg et al., 2015), and Morocco (Rozas et al., 2014), but also elsewhere.

²In the group lending method, borrowers form a group in which every member obtains an individual loan but is liable for the repayment of the loans from all other members. It thus allows lenders to cope with credit risk by outsourcing costly monitoring efforts to the borrowers.

³See, for instance, <https://cfi-blog.org/2017/01/09/growing-concerns-about-overindebtedness-in-mexicos-microfinance-sector/>, or <http://www.e-mfp.eu/blog/microfinance-mexico-beyond-brink>, both accessed on March 27, 2018.

plummet, from financial distress (Trautmann and Vlahu, 2013).

In the remainder of the paper, Section 2 presents the dataset and the Cox regression model, Section 3 discusses the results, and Section 4 briefly concludes.

2 Empirical setting

2.1 Data

The dataset, owned and maintained by Banco de México for regulatory purposes, covers all loans made via group lending from Mexican banks in the period from January 2012 to April 2017.⁴ Regulated banks bimonthly report information on every outstanding loan to the central bank, which yields $T = 32$ time periods. Aggregated on the group level, the dataset contains nearly 10 million panel observations. The analysis is run for 32,000 randomly drawn loan groups, equally distributed over all $t = 1, \dots, 32$ (1,000 per bimester). Since each group is observed repeatedly over time, the final sample contains 80,814 observations. After discarding information from groups after they defaulted, the final sample size is 59,796. Random sampling ensures that the subsample is an independently and identically distributed sample of the population of interest, which here is composed of all borrowers from regulated banks who were part of a loan group between 2012 and 2017. Further, since the p -value of a consistent and nonzero estimate converges to zero when sample size tends to infinity, random sub-sampling alleviates the problem that small and practically insignificant effects tend to be estimated as being highly statistically significant in large samples.

2.2 Methodology

Determinants of a loan group's ex-post risk to default are estimated via Cox's proportional hazards regression model. The dependent variable is the hazard to default, which denotes the rate by which groups default on a loan for the first time, given that a period t has elapsed since group formation. To filter out cases where repayment is merely delayed for a short period, only arrears of at least 30 days qualify as defaults. Hazard models account for changes of independent variables over time and thereby outperform static methods such as a logistic regression (Shumway, 2001). Another advantage of the Cox model is that no specific probability distribution of defaults needs to be imposed, which classifies it as semiparametric estimator. Conditional on a time-dependent

⁴Due to data confidentiality, information on the lending institutions is not disclosed.

random vector X_t and denoting time-to-default by T , the hazard is defined as

$$\lambda(t|X_t) = \lim_{\Delta t \rightarrow 0} \frac{P(t \leq T < t + \Delta t | t \leq T, X_t)}{\Delta t} \quad (1)$$

Following Iyer and Puri (2012), neighborhood spillover effects are measured as the fraction of loan groups in default for at least 30 days in the neighborhood of group i at time t , where a neighborhood is proxied by postal codes. To ensure that group i 's outcome does not alter the neighborhood default rate for this group, it is left out from the calculation. The “leave-one-out” neighborhood default rate is denoted by $D_{(-i)t}$. To allow for correlation among observations within a neighborhood, standard errors are clustered on the neighborhood level. Since the default of group i at time t might influence whether other loan groups in the same neighborhood default at t and thereby may cause reverse causality, the same models are run using the neighborhood default rate lagged by one bimester, denoted by $D_{(-i)t-1}$.

The models control for loan loss provisions reserved by the banks at the time of the loan disbursal, which reflect the banks' *ex-ante* perceived credit risk of borrowers (D'Espallier et al., 2011), and can be considered a function of otherwise unobserved borrower characteristics. Additional control variables are the loan's term to maturity, current maturity at time t , borrowers' loan cycles, inflation-adjusted interest rate, loan size,⁵ and group size (including a squared term to account for nonlinear effects of group size, as suggested by Impavido, 1998). Those variables are determined at the beginning of each loan round and are thus not affected by the eventual loan outcome. Further, the total number of loan groups in a neighborhood at time t is included, proxying the degree of local market penetration of group loans. The control variables are stacked in the vector Z_t . Finally, regressions include the vector $\psi = (\tau, \zeta, \xi)$, denoting time, state, and bank fixed effects (indexed by t , s and b , respectively). The model elaborates to

$$\lambda(t|D_{(-i)r}, Z_{it}, \psi_{tsb}) = \lambda_0(t) \exp(\beta D_{(-i)r} + Z_{it}\delta + \tau_t + \zeta_s + \xi_b), \quad \text{for } r \in \{t, t-1\} \quad (2)$$

where $\lambda_0(t)$ is the “baseline hazard”, conditional on all independent variables being zero.

Table 1: Descriptive sample statistics

	Mean	SD	Median	N
Loan defaults (%) ^a	2.99	16.93	0.00	59,796
Neighborhood default rate (%) ^a	16.32	11.49	14.40	59,796
Neighborhood default rate _{t-1} (%) ^a	15.71	11.43	13.86	59,790
Initial loan loss reserves (%)	1.22	3.56	0.85	53,161
Real interest rate (%)	86.22	18.86	80.99	59,796
Term to maturity (days)	133.64	42.67	112.00	59,796
Current maturity at t (days)	73.63	46.37	70.00	59,796
Loan amount (in MXN)	9756.49	5363.16	8382.75	59,796
Length of bank relation (cycles)	6.29	4.78	5.00	59,796
Group size	10.66	6.14	9.00	59,796
Number of loans in neighborhood	97.14	115.78	57.00	59,796

Note: MXN20 $\approx$ \$US1. ^a Only arrears $\geq$ 30 days.

3 Results

Table 1 summarizes the random sample. 3% of the observations involve a default of at least 30 days. Loans are small (9,756 Mexican pesos, or less than \$US 500) and have a short maturity (134 days), both of which are typical group credit features. They are expensive even for international microcredit standards (86% inflation-adjusted annual interest rate), which is peculiar to the Mexican market (Angelucci et al., 2015). Groups are on average composed of 11 members, the majority of whom are experienced borrowers that have advanced to their sixth loan cycle at the mean. The latter means that most borrowers have built a credit history, which explains the banks' relatively low average loan loss reserve ratio of 1.2% of the loan amount.

Figure 1 shows exemplary snapshots of the geographic distributions of defaults aggregated on the municipality level in two federal states, Veracruz and Chiapas. Both states feature important microfinance markets, with Veracruz being Mexico's largest in terms of volumes and number of clients. While only illustrative, the maps make some geographic clustering of delinquencies evident—for instance, in the north and south of Veracruz, and in western and northern Chiapas.

Table 2 reports the Cox regression results in terms of hazard ratios, obtained by exponentiating the estimated coefficient vector. For both the contemporary and the one-period-lagged neighborhood default rate the estimated coefficients are large and

⁵Both interest rate and loan size are averaged within a loan group, since loan terms can differ across group members.

Figure 1: Group loan default rates on the municipality level in the states of Veracruz and Chiapas, February 2017. Shades of red represent quintiles of default rates; the darker the higher the default rate.

significantly different from zero. Given other loan characteristics, the present default rate within the neighborhood increases the chance of a loan group’s default at a given point in time 23.3-fold (6.1-fold if fixed effects are included). Similarly, the lagged neighborhood default rate increases the default rate by 15.4 times (7.1 times if fixed effects are included). To illustrate, the latter says that a 1 percentage point increase in the neighborhood default rate increases a group’s hazard to default in the following two months by approximately 15.4 (7.1) percent. The analysis was also conducted on the full sample, which qualitatively reproduced the results and is therefore not reported here, the main difference being that all p -values were much smaller due to their aforementioned large sample property.

The results suggest that geographic spillovers contribute a significant share to individual credit risk. Some explanations in line with the literature can be put forward: (1.) Group members borrow simultaneously from different lenders, and thus expose different loan groups to credit risk. Anecdotal evidence suggests that multi-borrowing is widespread among Mexican borrowers, and often associated with borrower over-indebtedness.⁶ Borrowers may also resort to informal loans to repay a bank loan and thereby accumulate debt unsustainably (Arnold and Booker, 2013). (2.) Borrowers strategically default when they learn about defaulting loan groups in their neighborhood,

⁶See sources in footnote 3.

Table 2: Hazard ratios of group loan default determinants in Mexico 2012–2017

	(1)	(2)	(3)	(4)
Neighborhood default rate	23.26*** (17.86)		15.40*** (12.94)	
Neighborhood default rate _{<i>t</i>-1}		6.054*** (9.31)		7.083*** (8.49)
Initial loan loss reserves	2.127*** (20.90)	2.158*** (20.96)	2.107*** (16.49)	2.132*** (17.09)
Real interest rate	0.855 (-1.51)	0.835 (-1.52)	0.779 (-1.78)	0.833 (-1.29)
Current maturity	0.995*** (-7.11)	0.994*** (-8.13)	0.993*** (-8.42)	0.993*** (-8.70)
Term to maturity	1.005*** (6.85)	1.006*** (6.70)	1.006*** (7.71)	1.007*** (7.95)
Loan size	1.089 (1.19)	1.079 (1.07)	0.974 (-0.35)	0.977 (-0.31)
Length of bank relation	0.951*** (-4.50)	0.941*** (-5.34)	0.958*** (-3.71)	0.957*** (-3.80)
Group size	1.234*** (6.03)	1.233*** (6.02)	1.361*** (7.89)	1.371*** (7.99)
Group size squared	0.996** (-2.88)	0.996** (-2.83)	0.994*** (-4.09)	0.993*** (-4.13)
Loan groups in neighborhood	1.010 (0.33)	1.013 (0.46)	0.990 (-0.33)	0.982 (-0.59)
Time FE	No	No	Yes	Yes
State FE	No	No	Yes	Yes
Bank FE	No	No	Yes	Yes
χ^2 likelihood ratio	1172.52	859.28	1788.69	1623.25
Pseudo R ²	0.052	0.044	0.070	0.066
# of defaults	1, 535	1, 535	1, 535	1, 535
Total <i>N</i>	53, 148	53, 142	53, 148	53, 142

Source: bi-monthly data from January 2012 to April 2017 reported to the central bank by all banks that grant group loans in Mexico. Exponentiated coefficients (i.e. hazard ratios) reported. Due to right-skewness, the following variables are expressed in logs: Initial loan-loss-reserves, real interest rate, loan size, loan groups in neighborhood. Standard errors are clustered on the neighborhood level. *t*-statistics in parentheses. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

perhaps expecting that their local bank branch will close due to poor performance. However, the negative coefficient of current maturity in Table 2 implies that groups are more likely to default the sooner the loan is to mature, and thus the costlier strategic default would be. This suggests that, at least on average, strategic default is not common.⁷ (3.) Borrowers from different loan groups within a neighborhood are subject to covariate risks. A common shock then exposes several loan groups at the same time to increased default risk.

Banks so far appear to be able to cope with group lending risk: first, loan loss reserves significantly explain ex-post credit risk, and second, longer bank relationships of group members go along with a lower probability of group default, all else equal. Banks may also be able to deal with geographic spillovers as long as these remain regionally bounded, by cross-subsidizing high-default districts with low-default ones. However, the existence of such spillovers make the market vulnerable to an economic downturn. Experiences from other contexts (notably India and Nicaragua) shows that the microfinance industry can forfeit public legitimacy when accounts of coercive practices and sky-high interest rates charged to poor and indebted borrowers become politicized issues (Mader, 2013; Servet, 2015). Such events may create hot spots of spiking default rates due to local spillovers. If these spillovers cause market-wide contagion, they may swiftly proliferate into a repayment crisis.

It is therefore advisable for lenders to monitor trends in regional default rates and explore its underlying factors, in order to implement counteraction when default rates rise. The findings are also of interest for financial regulatory authorities, since regulated banks that are active in group lending also intermediate clients' deposits, which are at stake when a default crisis causes financial distress of banks, further exacerbated by the risk of a bank run. For instance, regulators could install an early warning system by asking banks to assess and report the extent to which clients take multiple loans from other institutions, including unregulated lenders.

4 Conclusion

Applying a Cox proportional hazards model to regulatory data on group loans granted by Mexican banks between 2012 and 2017, I find that ex-post credit risk is substantially explained by geographic spillovers in the neighborhood. While group lending features specific characteristics such as social ties between borrowers, weak legal debt enforcement, and absence of collateral, the findings are also relevant for other financial

⁷This corroborates the finding of Allen (2016).

applications such as general retail banking. Future research could explore underlying transmission effects of credit risk and to what extent they reflect, or perhaps cause, credit risk contagion. Data from previous repayment crises might be harnessed to assess whether geographic spillovers can be used to forecast a crisis. In addition, the role of multiple borrowing in explaining spillovers needs to be better understood.

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